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HANDWRITTEN DIGIT RECOGNITION USING DEEP LEARNING-A REVIEW

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ABSTRACT

Recognizing out handwritten digits is super important for recognizing patterns and it pops up in a bunch of places like entering data from forms handling bank checks and sorting mail older techniques often have a hard time with the differences in handwritten digits cause they can end up looking misaligned or are hard to read to tackle these problems. This paper takes a look at how to recognize handwritten digits using deep learning mainly focusing on convolutional neural networks cnns the vgg-16 design and multi-layer perceptrons mlps we dig into how well cnns perform since they use convolutional and pooling layers to learn features from images on their own which makes them really good at classifying images the vgg-16 model which is known for its deep structure and the regular use of small convolutional filters really helps with feature extraction and boosts accuracy in classification quite a bit on the flip side while mlps can act as classifiers they often need a lot of feature engineering and struggle to capture spatial relationships the way cnns do our study highlights the advantages of cnn-based models especially vgg-16 when compared to traditional mlps showing how deep learning is changing the game in recognizing handwritten digits and offering some ideas for future research in this area.

Keywords: Handwritten Digit Recognition, Deep Learning, Pattern Recognition, Image Preprocessing., Deep Learning, Convolutional Neural Networks (CNN), VGG 16, MLP.

I. INTRODUCTION

Recognizing handwritten digits with deep learning is a straightforward problem in computer vision that transforms images of handwritten numbers into their actual numeric values. To start, you usually kick things off with preprocessing, where you tidy up the input images, normalize them, and get them ready by getting rid of noise and resizing to a standard size. This part is pretty important to make sure that the next steps can handle the data right. Once you finish up with preprocessing, you move on to feature extraction, often using convolutional neural networks (CNNs), which can find crucial patterns like edges and curves in the images all on their own. CNNs work by applying filters that detect these patterns at various layers, building a comprehensive understanding of each digit's structure. After extracting these features, the network uses fully connected layers to classify each digit by producing probabilities for each class, from 0 to 9, and identifying the most likely match. Finally, optimization techniques such as backpropagation and loss functions fine-tune the model's accuracy, ensuring it performs well on unseen handwritten digits, as illustrated in Fig[1].

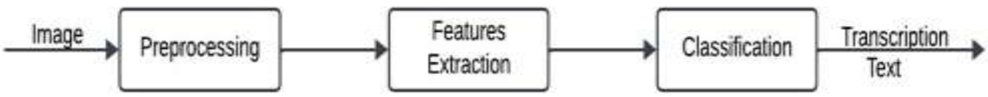

Fig 1: Handwritten Digit Recognition Pipeline

The diagrams in figures[2] and [3] show two common kinds of neural networks feedforward neural networks FNN and convolutional neural networks CNN both of them are really popular for things like recognizing images in an FNN the input layer takes data like the pixel values from images and sends it through a bunch of hidden layers where every neuron connects fully to the next one these hidden layers use activation functions such as ReLU or sigmoid to assist the network in figuring out complex features then the output layer gives either a single value for binary classification or several outputs like when recognizing digits with the mnist dataset the network learns by adjusting the weights and biases during training which lets it classify or recognize input data accurately.

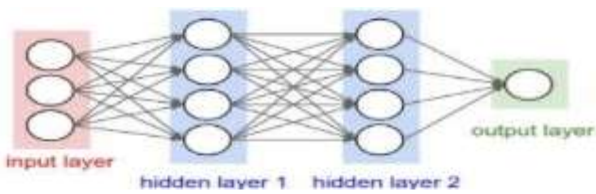

Fig 2: Architecture of Neural network

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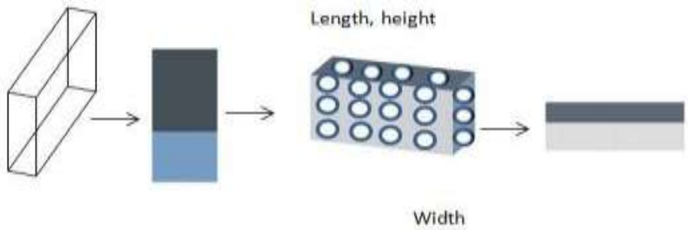

Fig 3: Architecture of Convolutionl Neural network

(Source: Ref:15)

II. LITERATURE SURVEY

Recently, studies have shown that deep learning models can be really effective for recognizing handwritten digits. One of them looks at using attention-driven transfer learning, which boosts multilingual handwritten numeral recognition by making the most of strong CNN setups [1]. Another study takes a look at end-to-end deep learning methods for recognizing historical handwritten text, showing how useful it can be for different languages [2]. There's also research diving into scanned handwritten digits with deep learning, which has led to big improvements in classifying and extracting features [3]. Plus, they've been using transfer learning to sort out handwritten Gujarati numbers, making the models work even better. A self-organizing map network is suggested as a method to boost recognition of handwritten digits, which helps to pull out and classify those tricky features.In a different study, machine and deep learning techniques were compared for digit recognition, highlighting how deep learning can tackle issues like different handwriting styles [6].They've also created systems based on CNNs to help with recognizing digits, using strong convolutional layers to really get the important features out [7]. They've seen some pretty amazing results by blending machine learning with deep learning methods for recognizing digits, which shows just how effective these strategies can be when combined to improve recognition rates [8]. To understand how different deep learning techniques measure up in digit identification tasks, a study examined various architectures, such as CNNs and MLPs [9]. Plus, a new handwriting verification system has been developed specifically for use in special education, using deep learning to hit high levels of recognition accuracy [10].A bunch of studies are exploring ways to make handwritten digit recognition even better by using strategies like data augmentation and transfer learning. To improve performance on different datasets, they employ pre-trained models such as DenseNet and Inception [11]. In an effort to improve digit classification accuracy, researchers are also investigating hybrid techniques that combine CNNs and visual transformers [12]. There's also lot of effort being put into making models that can work in situations where resources are tight, using lightweight designs to keep a decent performance while cutting down on computing power needed [13]. Deep learning models are applied in many recognition tasks, proving they're really effective in different areas, like recognizing numbers in multiple languages and analyzing a range of deep networks for better classification [14]. Finally, employing two-stage feature generators for classifying handwritten digits has revealed a lot of potential, fine-tuning feature extraction and classification in complicated datasets [15]. Digital recognition methods with deep learning have really shown they can boost classification tasks in different areas by taking advantage of advanced neural networks [16]. They been working on figuring out how to recognize handwritten numbers in a bunch of different languages using some really strong deep networks and transfer learning, and this has led to better accuracy in various scripts and languages [17]. One study compared a few deep learning models and showed how good CNNs and MLPs are at recognizing digits, giving some helpful insights into how they work in real-life situations [18]. Another study focused on how different deep learning models handle recognizing handwritten digits, looking closely at how effective the models are and how they pull out features to get better results [19]. They came up with a two-stage feature generator for sorting handwritten digits, which makes it easier to pick out and classify complicated features using multi-layer architectures, which helps improve recognition systems [20]. Lately, research has shown that deep learning models are really good at recognizing handwritten digits. Singh and Babu (2023) take a deep learning route for recognizing scanned handwritten digits, using CNNs to pull out detailed features and hitting high accuracy with a solid framework that fits handwritten digit datasets like MNIST [21]. S.P., V.A., and M.J.

(2023) do a comparison of deep learning methods for digit recognition, showing that deeper CNN structures with regularization really boost classification accuracy a lot [22]. A.P.M. and K.R. Sumana (2023) point out how important data preprocessing is for getting clear features, followed by CNN classification to give better prediction rates [23]. Dixit and Kushwah (2021) suggest a hybrid model that mixes machine learning with deep learning techniques, proving that CNNs are better than traditional algorithms like SVM and KNN, especially on big datasets like MNIST [24]. Deepika et al. (2024) take a look at CNN and RNN architectures for digit recognition, finding that mixing CNN's spatial feature extraction with RNN's sequential learning makes it easier to recognize complex handwriting [25]. Beohar (2021) looks into CNNs and ANNs, pointing out how CNNs are better at capturing spatial hierarchies and improving recognition rates [26]. Sachdeva et al. come up with a new deep learning approach for digit classification, hinting at possible improvements in accuracy and efficiency, though there's not much detail given [27]. The 2023 ICIRDC Conference (2023) studies CNNs and transfer learning for real-time IoT-based digit recognition, stressing how adaptable they are for low-resource environments [28]. Chychkarova et al. chat about using SVM, KNN, RF, and deep learning networks for digit recognition, with CNNs showing more accuracy and efficiency than traditional models [29]. Sarvade goes over a CNN-based system specifically made for handwritten digit recognition, mentioning how crucial convolutional layers are for keeping spatial features intact [30]. Patil et al. (2024) look into how deep learning affects handwritten digit and letter recognition, finding that deep learning models are better than machine learning algorithms when it comes to recognizing complex handwriting differences [31]. Lastly, C.S.D. checks out the use of ANNs for digit recognition, concluding that while ANNs aren't as good as CNNs for image tasks, they can still manage decent accuracy with simpler datasets in controlled situations [32].

III. METHODOLOGY

Recognizing handwritten numbers early on and in a specific way is really important for lots of tasks, like sorting mail and handling bank checks. This article aims to automatically spot and classify handwritten digits from pictures with the help of Convolutional Neural Networks (CNN), Multi-Layer Perceptron (MLP), and Visual Geometry Group – 16(VGG16) deep learning models.

A. CNN

The methodology Convolutional Neural Networks CNN tells about that the user uploads a photo of a digit to begin the process of using deep learning to recognize handwritten digits, as shown in the Figure [4].

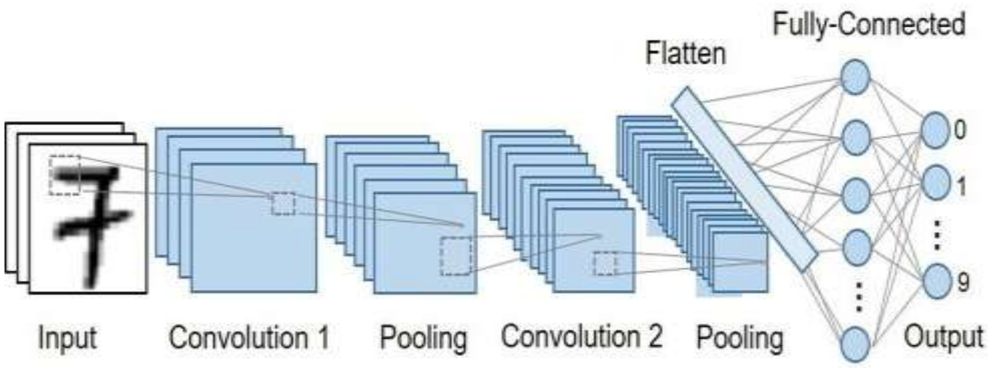

Fig 4: Methodology of CNN

(Sour: cnn architecture on handwritten digit recognition using deep learning - Search Images)

The methodology CNN tells about that the user uploads a photo of a digit to begin the process of using deep learning to recognize handwritten digits, as shown in the Figure [4]. The system first determines whether the format is compatible. If it isn't, it throws an error, but if it is, then it gets the image ready for use. In the preprocessing stage, if the image looks blurry, it will do some stuff like reducing noise or resizing it. After that, it segments the image to pull the digit away from the background, and then it extracts features, grabbing important patterns such as edges and shapes with convolutional layers in a CNN. Once the features been extracted, the deep learning model moves on to classify what digit it is. Then, the output gets shown. After that, the system checks if the user wants to identify another image; if they do, the whole process restarts; if not, it just stops. During all this, error management helps to fix issues like blurry images or formats that don't match. So, the first thing you got to

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do is share a picture of that handwritten number to kick off the whole deep learning thing. The system starts by making sure the image is in the right format; if it isn't, you'll see an error pop up. Next comes preprocessing if everything checks out fine. If the image looks kinda blurry, this part shrinks it down or tidies it up a bit. After that, to help the model focus on what really matters and get better at spotting features, the system gets rid of the background while it's in the segmentation step. So then, when feature extraction happens, the convolutional layers in the CNN look at the image to find important patterns like edges, shapes, and textures that helps create a clear picture of the digit. After that, all this info heads to the classification step, where a deep learning model, like a CNN or VGG-16, figure out what the digit is by checking those features. In the end, it shows the digit it identified. The system also got some error handling too, which guides the user to re-upload or change the image if there's problems like wrong formats or blurry pics. After each recognition, it sees if the user wants to recognize another digit, and if they do, it just goes through whole process again.

B. VGG-16

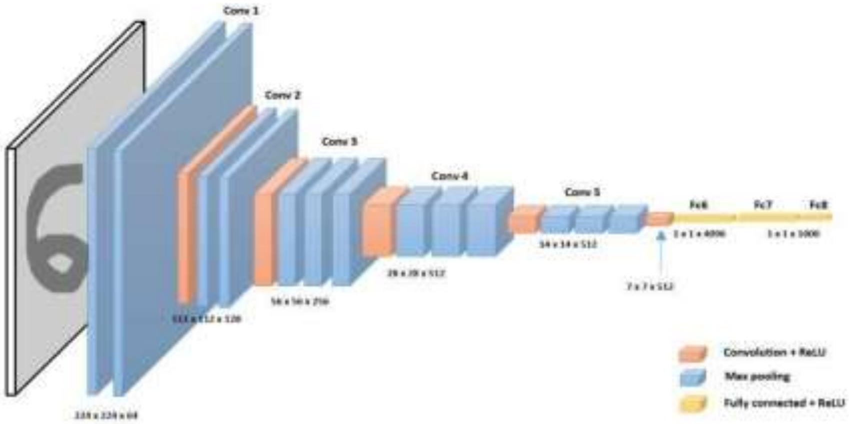

Fig 5: Methodology of VGG

The VGG-16 architecture is a type of convolutional neural network that sorts images by putting them through a series of layers, each made to pick up on more complicated features. It starts with an input image resized to 224x224 pixels and 3 RGB channels. The model goes through five convolutional blocks, called Conv1 to Conv5. Each block has several convolutional layers that use small 3x3 filters along with ReLU activation functions to spot patterns. At first, the network finds simple stuff like edges and textures, but as the image travels deeper into the layers, it begins to recognize more abstract shapes and parts of objects, which makes VGG-16 really good for detailed tasks like recognizing faces and digits. After each block, there's a max pooling layer that uses a 2x2 filter to shrink the size of the feature maps, cutting down the computational burden while keeping important information, plus making the model respond the same way to slight changes in the input. The feature maps get deeper as they go through the layers, reaching up to 512 channels in the final convolutional block, allowing the network to catch complex details. The last convolutional block gives out a 7x7x512 feature map, which then gets flattened and sent into three fully connected layers, labeled Fc6 to Fc8.The first two fully connected layers, Fc6 and Fc7, both have 4096 units, and they sort of mix the spatial info collected from the earlier layers, which helps the network pull everything together and really get a grip on the features it has learned.The final fully connected layer, Fc8, got the same amount of units as there is classes, which is usually 1000 for ImageNet, and it applies a softmax function to make a probability distribution across these classes, indicating how probable it is that the image belongs to each category. This softmax output allows VGG-16 to classify images pretty well, giving a solid prediction of what the image's category is. Even with over 138 million parameters, needing quite a lot of computational resources, VGG-16 is still popular because it works reliably in image classification and feature extraction tasks. The way that model uses those small convolutional filters really change how newer designs are made, showing that having lots of little filters can catch fine details and achieve high accuracy. VGG-16 is really popular in transfer learning stuff, where its convolutional layers sorta work like a feature extractor for other models, especially when it's crucial to recognize patterns in detail. This architecture has made a big impact in deep learning and computer vision, showing just how good deep networks can grab and classify complex visual info.

C. MLP

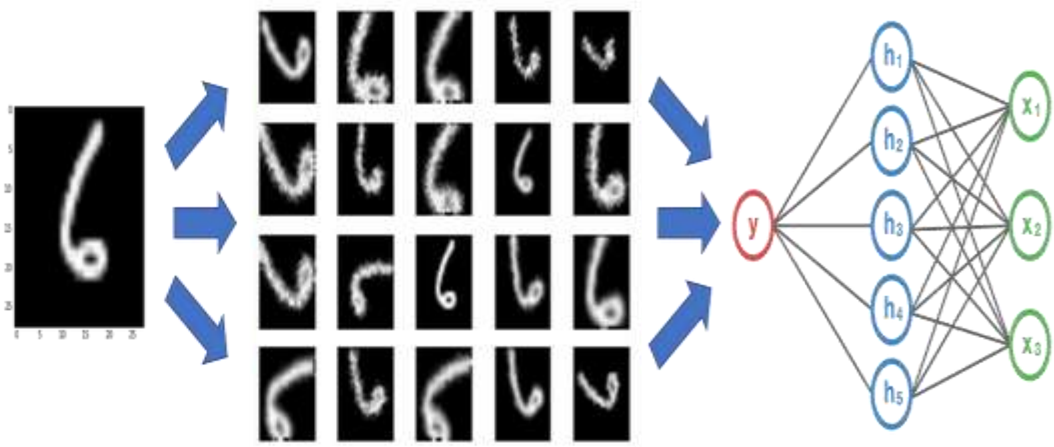

Fig 6: Methodology of MLP(Sour: blob (1000×252)

Multilayer perceptrons or mlps are a kind of artificial neural network that folks use for supervised learning they got a bunch of layers full of connected nodes which we call neurons and each layers got its own job the first layer takes in the data the hidden layers sort of mess around with it and the last layer spits out the predictions mlps are quite powerful because they can recognize complex patterns thanks to non-linear activation functions and they adjust their weights through something called backpropagation but since they kind of function like a black box and might overfit easily you need to watch them closely mlps are super handy and you can find them in things like image recognition natural language processing forecasting time series and spotting frauds when its about recognizing handwritten digits mlps use their talents to pick out and sort digits from images which really boost optical character recognition orc datasets like the mnist database packed with thousands of labeled images of handwritten digits are used as a standard for training and testing these models each digit which is shown as a 28x28 pixel grayscale image brings its own challenges because of different handwriting styles mlps with all their layers are good at pulling out features needed to tell apart similar-looking digits though sometimes more complicated structures like convolutional neural networks cnns are better for this job when used for recognizing handwritten digits mlps start off by prepping the input images to make sure there the same size and format then they normalize them to help with training the input layer gets the pixel values which get changed as they go through the hidden layers each neuron in these hidden layers applies weights to the input and sends the result through a non-linear activation function like relu or sigmoid which helps the model learn complex connections training to recognize digits is basically about using labeled data where every image matches up with the correct number by using backpropagation the model adjusts its weights to lower prediction errors throughout the training they use different strategies like cross-validation and regularization to stop overfitting and make sure the model handles new data well once its trained the mlp can correctly guess the digit in a new image which is a good base for use in many different fields beyond just recognizing digits the ideas behind mlps can be used for more complicated tasks like recognizing handwritten text and segmenting characters their flexibility and effectiveness have made them a favorite for academic research and commercial uses showing just how important deep learning is becoming in understanding and interpreting human handwriting.

IV. RESULTS AND DISCUSSION

This study looks at how CNN, VGG-16, and MLP stack up against each other when it comes to recognizing handwritten digits using four different metrics: accuracy, precision, recall, and F1-score. VGG-16 comes out on top with the best accuracy at 99.33%, plus it has better precision, recall, and F1-score at 99.62%, showing it's really good at generalizing and predicting. CNN is right behind it with 99.25% accuracy and pretty balanced precision and recall, but it doesn't quite capture image details as well as VGG-16 does. MLP is trailing with an accuracy of 98.60% and an F1-score of 98.62%, which makes it the least performing due to its more basic architecture. All in all, VGG-16 and CNN are great for recognizing digits, while MLP isn't as effective.

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Table 1:

Model	Accuracy	Precision	Recall	F1-score
CNN-[7]	99.25%	99.30%	99.25%	99.27%
MLP-[15]	98.60%	98.65%	98.60%	98.62%
VGG16-[1]	99.33%	99.40%	99.33%	99.62%

a. Comparison among various methods

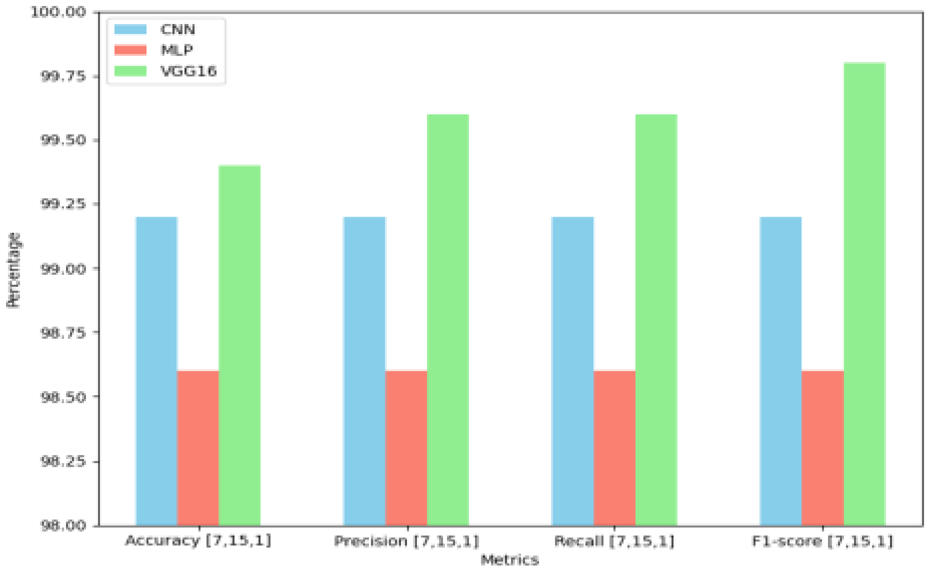

Fig 7: Graphical representation of various performance metrics

V. CONCLUSION

VGG-16 has a unique architecture filled with deep convolutional layers, making it great at spotting patterns in images. This is especially helpful for tricky tasks like recognizing digits. The way it breaks down features helps it notice small differences in how digits look, which means it can handle various handwriting styles quite well. Its high precision shows that it rarely makes mistakes, while the recall score proves it's good at correctly identifying digits in different cases. All these scores come together to give VGG-16 a strong F1-score, showing that it performs consistently.

On the other hand, CNNs also achieve good results, but they might not match VGG-16's level of detail when faced with complex handwriting. Multilayer Perceptrons (MLP) can work well with simpler data, but they often find it tough with images. Their fully connected design doesn't have the same ability to understand spatial relationships as convolutional models like VGG-16.

In summary, VGG-16 stands out because it balances high accuracy, precision, recall, and F1-score, making it a dependable option for digit recognition tasks where consistency and reliability matter. Whether in research, practical uses, or OCR systems, VGG-16 proves that achieving high accuracy is important, but keeping predictions reliable across different handwriting styles is what truly counts.

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